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SOME FEASIBILITY CONSIDERATIONS
FOR SELECTING AND MAINTAINING
MEDICAL DIAGNOSTIC SYSTEMS

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and
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The major problem areas for initiating, maintaining and evaluating a medical diagnostic system (MDS) are presented. In particular, the decision-making activities are modeled along with the problems of paramedic utilization, cost comparisons, and a staff planning model for the medic-paramedic-computer team. Methodical data collection procedures are required if these modeling efforts are to be validated and implemented.

1. INTRODUCTION

This paper is an attempt to discuss and synthesize some issues connected with medical diagnostic systems. We point out in the onset that this is a framework for a large class of operational problems. Although alternative formulations are possible and perhaps even desirable, given the embryonic state of the art some large scale structuring is necessary.

Effective medical care is one of the greatest concerns of society today, and this depends on the accuracy and efficiency with which we are able to detect, diagnose, and treat diseases. Years ago, these functions were conducted solely by a physician. Although the physician today still maintains the responsibility for these functions, his role is that of a medical diagnostic system (MDS) team leader. As such, he coordinates the collection, dissemination, and correlation of information from which he bases his evaluations. In addition to the nurses, technicians, and other supporting personnel, a number of activities are conducted in conjunction with computers and other types of machines. Thus, the MDS today is actually a complex man-machine system.

The current state of the art in seeking improvement of medical diagnosis involves the following three major problem areas:

(1) causes and effects of diseases

(2) methods of utilizing disgnostic information

(3) methods of evaluating MDS's.

The first and oldest and most basic of these is the problem of correctly identifying a disease or state of health for a given set of symptoms. The difficulties here are due to our lack of a complete understanding of existing diseases and ailments. Although through medical research we are gaining a greater understanding of causes and effects of diseases, this problem area will prevail as long as new diseases continue to develop.

The second area arises as a consequency of our progress in the first. As we learn more about diseases and ailments, we simultaneously increase the number of alternative symptom-disease combinations that the physician must consider in diagnoses. Thus, the complexity of the decision problems involved in diagnosis increases with the amount of available information. These decision problems, particularly with the advent of the digital computer, rather naturally warrant a decision theoretic formulation. From early observations by Ledley and Lusted [18], numerous efforts to computerize diagnostic procedures have been reported (see Lusted [19]). These studies include mathematical models for classifying patients into disease categories [2, 10, 15] and computer procedures for monitoring, retrieving, and displaying medical data [25, 26, 27]. The actual implementation of results in this area is somewhat limited and spotty, not the least of which is due to a lack of appropriate data. Moreover, the concept of computerizing diagnostic procedures in medicine has not yet gained wide acceptance among physicians. Still, the trend toward higher degrees of automation and larger scale diagnostic systems appears to be inevitable [4].

As new diagnostic system designs and developments emanate from these first two areas, a third problem area exists in the evaluation and selection of designs for given medical environments. Like any other system, the analysis of an MDS requires synthesis by making comparisons among alternative systems or design configurations. This requires a set of, ideally standard, performance measures and measures of effectiveness. The motivation for developing an MDS in the first place was to produce a system that:

(1) diagnoses with accuracy and efficiency "at-least-as-good-as" that of a sole physician, (2) provides for improved utilization of medical manpower, and (3) ultimately can be economically justified. Thus, an overall measure of effectiveness should somehow reflect these objectives. The most commonly used performance measure for an MDS has been percentage misclassifications or errors in diagnosis. Other measures that have been studied are health status [13], relative importance of symptom disease combinations [11], and severity of illness [12]. In addition to these measures that relate to diagnostic accuracy, numerous indices have been developed for assessing aspects of overall medical and health care systems (see [8, 14, 20, 21, 23]).

It is of vital importance that our efforts in this third problem area parallel those of the first two. Several feasibility issues must be considered before a system reaches the implementation stage, and quantitative methods are needed for making such determinations.

In this report we attempt to place the problem of medical diagnosis in proper perspective for examining operational issues. We discuss a general model that describes the decision making activities involved in an MDS, identify some measures of effectiveness, and discuss some models for dealing with feasibility issues in these systems.

We shall present a model of an MDS in Section 2 comprised of a number of special purpose components. A special purpose component involves complex decision processes which are described in Section 3 along with some measures of effectiveness. In Section 4, we summarize a preliminary approach for examining feasibility issues for anlayzing an MDS, followed by some concluding remarks and recommendations in Section 5.

2. MDS MODEL

At one time, essentially all diagnostic functions were conducted by a single physician who received a patient with given symptoms, decided on the set and sequence of appropriate tests, and ultimately reached a diagnosis - perhaps with the benefit of a colleague's opinion. The decision flow may initially and schematically be viewed as indicated in Figure 1.

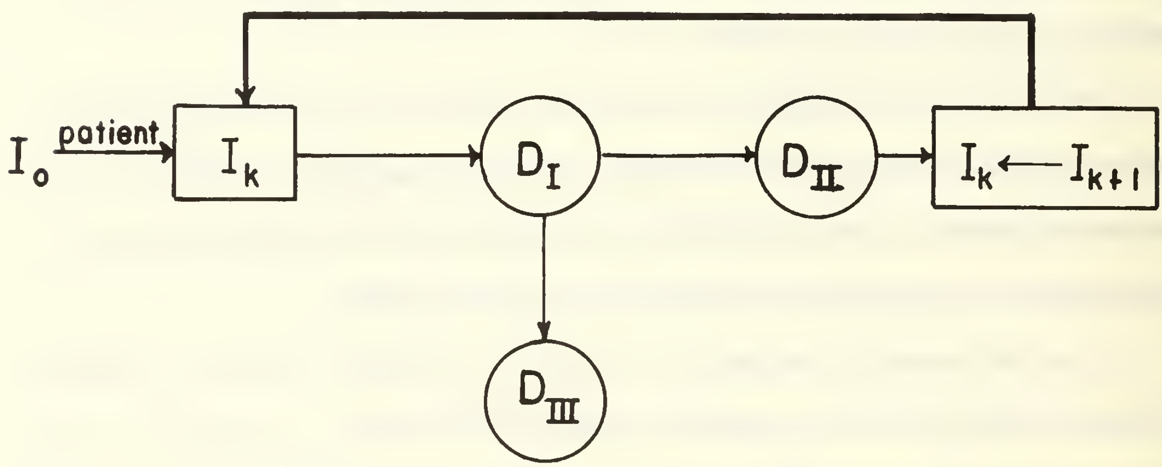

Figure 1: Basic Diagnostic Procedure

Here I_0 represents the initial amount of information, and the sequence I_1, I_2, ... represents the sequence of information amounts updated from testing. The first type of decision, D_1, is the decision of whether more clinical testing should be conducted. If more testing is deemed necessary, then D_{II} represents the decision corresponding to a choice and sequence of tests. Ultimately, the basic decision, D_{III}, must be made on the diagnosed state of the patient.

In Section 3, we will expand Figure 1 and discuss the information gathering, updating, and decision-making aspects of this basic diagnostic procedure in the light of a special purpose decision model. At present, we will expand this basic diagnostic procedure in a different direction - one which will allow it to include screening, use of paramedic-computer aid, and employment of several special-purpose decision submodels. We shall refer to this model as the general purpose model or MDS model - one which in theory considers all types of diseases ranging from the common cold to neurological disorders. The decision flow for the general purpose MDS model may be viewed macroscopically as in Figure 2.

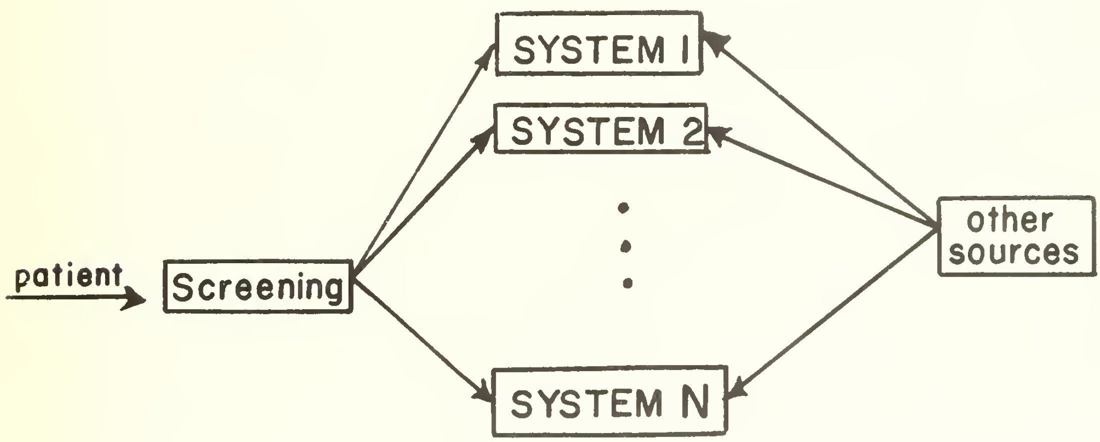

Figure 2: Overview of a General Purpose Medical Diagnostic System (MDS)

We see from Figure 2 that the MDS model is comprised of several special purpose component systems, each specializing in the diagnosis and treatment of a given class of ailments. One such special purpose system involves the diagnosis and treatment of coronary heart disease discussed in Section 3. Crossovers among the component systems do exist and are desirable. They allow for initial mis-assignment to the wrong system.

The most noted example of large-scale screening is the multiphasic screening procedure incorporated by Kaiser [5]. This procedure not only acts as a potential time-saver and diagnostic aid, but also provides for the systematic medical data gathering and updating procedures that are so vital to the success and continued growth of an MDS. In Section 3, we shall discuss the importance of data and updating procedures in measuring the effectiveness of an MDS or special purpose system.

Understandably enough, more fundamental work has been done in the area of special-purpose models than for general purpose models. Since the latter requires a much more centralized environment than has yet been seen in the medical community, it is more difficult to model and validate. Ultimately, however, the costs and benefits of MDS will have to be explored. An attempt is made to do so in Section 4. It should be noted that Ledley [17] discusses some decision rules for general purpose models.

An important factor subsumed in the MDS model of Figure 2 is the use of a paramedic-computer team to hopefully aid in the accuracy and duration of the diagnostic procedure as well as to conserve the valuable time of the physician. Figure 3 is a schematic representation of medic-paramedic interaction.

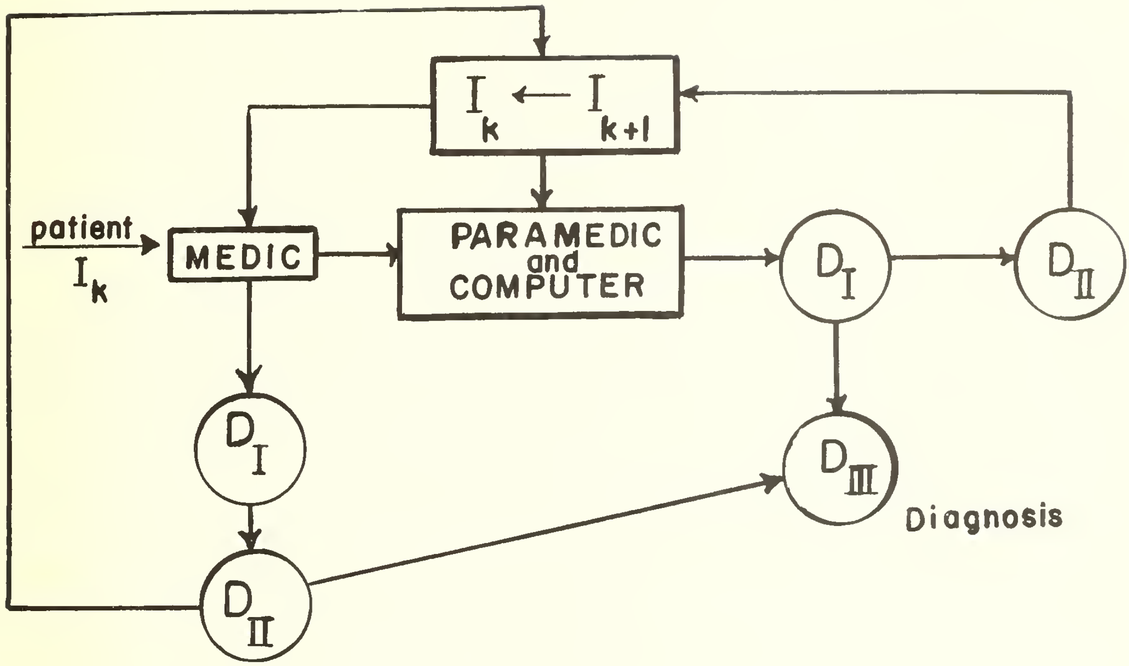

Figure 3: Medic-Paramedic Interaction in a Special Purpose System

The decisions D_I, D_{II} and D_{III} are as in Figure 1. In Section 4, we shall expand on Figure 3 and investigate the time-conserving role as well as the "potential" dollar-conserving role played by the paramedic-computer team.

3. A SPECIAL PURPOSE DECISION MODEL

In this section we discuss a special purpose model which could be, though not necessarily, a component of the more general MDS model discussed in Section 2. This special purpose model involves the diagnosis and treatment of coronary heart disease (CHD).

Like many medical diagnosis problems, the complexity and uncertainty involved in the diagnosis of CHD naturally suggests a decision theoretic formulation for analysis (see Lusted [19]). In this section we outline the general decision problems that exist in the diagnosis of CHD, and summarize a quantitative approach for dealing with these problems. This approach follows that of Thomas, et al. [24].

The flow of patients to a cardiac clinic is similar to the input to any other specialty clinic. A patient may be referred to the cardiologist by another doctor based on the results of a physical examination, or, if a person believes that he is suffering from a cardiac or cardiac-related illness, he may voluntarily seek the advice of the specialist directly. In either case, by the time a patient is admitted to cardiology, there is already certain data on him that is available to the physician without specified testing. From that point on, however, the diagnosis of a possible heart disease is a function of the doctor's ability to assign relative importance to an appropriate set of indicators. The patient and his health, costs of testing, and the available clinical procedures may have a bearing on the doctor's ability to diagnose correctly.

Several indicators, which are factors that are known to be related to the true state of a patient's heart, have been identified from the medical literature (see Condos and Knox [6]) and for the most part are universally accepted. Examples of these are race, age, sex, physiological dimensions, history of heart conditions, etc., as well as clinical and laboratory test results on such factors as EKG, cholesterol, and triglycerides. From these indicators, a matrix $S(k) = [s_{ij}^k]$ called a symptom complex is constructed where s_{ij}^k corresponds to outcome $j = 1, \ldots, n$ of test $i = 1, \ldots, m$ at decision point $k = 0, 1, \ldots$. A decision point occurs each time the cardiologist resolves choice, among a set of alternatives, having started initially at $k = 0$ for a given patient. This matrix contains the source of information upon which he bases his diagnosis.

The cardiologist then is viewed as a decision-maker who, for each patient, receives an initial amount of information $I_0 = f(S(0))$ from which he initiates a sequence of decisions, increasing the available information, $I_1, I_2, \ldots,$ as a result of testing. This sequence of decisions consists of three distinct types of decisions, as shown in Figure 1 of Section 2, with $I_k = f(S(k))$. In the parlance of decision theory the combination of D_I and D_{II} is called the "sampling plan", and D_{III} is the "terminal decision". Note that once D_{III} has been made for a given patient, any reentry to the system will commence a new diagnostic period with $k = 0$. Presently, the decisions are reached almost exclusively on the basis of human judgment, and it is, therefore, of interest to improve ways of aggregating, weighting, and utilizing the information yielded by diagnostic tests.

Since some of the elements of $S(k)$ are qualitative, it is advantageous to transform $S(k)$ to a quantitative matrix in such a way that the likelihood of CHD is an increasing function of the value of each element of the matrix. One such transformation proposed by Condos and Knox [6] is given by

$$z_{ij}^{k} = \frac{P\{D | t_{ij}\}}{\min_{\ell}[P\{D | t_{i\ell}^{k}\}]} \tag{3.1}$$

where t_{ij}^k represents outcome j of test i at decision point k. The revised symptom complex $Z(k)$ is easier to treat than $S(k)$.

Formally, one arrives at the first decision rule, D_I, by finding the function $f(S(k))$ that relates the symptom complex to some value I_k, and then determining a value function $V(I_k)$. From these functions, we may, in theory, continue to obtain additional information until an amount I_{k*} is obtained such that

$$\begin{aligned} V(I_{k*-1}) - V(I_{k*}) &\leq 0 \\ V(I_{k*+1}) - V(I_{k*}) &\leq 0 \end{aligned} \tag{3.2}$$

where $V(I_k)$ is a value function for I_k. In other words, we test until the marginal value of additional information is offset by the required effort in obtaining information. Certainly the choice of $V(\cdot)$ is not an easy one since it reflects the attitude of the cardiologist toward risk. One viable value function for this purpose is the "expected value of sample information" (see Raiffa [22]).

The second desired decision rule, D_{II}, is one that, according to Lusted [19], has not previously received much attention. At a given decision point k, we have a finite number of tests that can be conducted. Let $\bar{c}_i^k$ be the expected effort of conducting test i and π_i^k the probability that test i provides conclusive evidence for $I_k \geq I_{k*}$. We want to specify an ordering among these tests so that the expected effort required to reach $k*$ is a minimum. Thus, we have a proposition which states as follows:

A minimum expected effort sequence is given by ordering the tests so that

$$\pi_j^k/\bar{c}_j^k \geq \pi_{j+1}^k/\bar{c}_{j+1}^k, \tag{3.3}$$

for all $j = 1, 2, \ldots.$

The proof of this is given by Chu [3].

Finally, we have the third desired decision rule which is actually the result of the diagnosis process. Three basic methods have been employed for deriving this rule. One method consists of using pattern recognition and discriminant analysis techniques [9, 16]. Although this method is a most attractive one in terms of simplicity offered, it is limited by the rather restrictive normality assumptions required. A second method is based on utility theory, and it has a major drawback in that the assessment of multidimensional utilities is very difficult. This is particularly true for applications to a serious medical problem [1]. The third and most widely used is the Bayesian method [19]. Here we assume some threshold, or cutoff probability, γ and base our decision on whether or not at a decision point k the posterior probability of having CHD

$$P\{D|t_{ij}^k\} = \frac{P\{t_{ij}^k|D\}P\{D\}}{P\{t_{ij}^k|D\}P\{D\}+P\{t_{ij}^k|\bar{D}\}P\{\bar{D}\}} \tag{3.4}$$

exceeds this value γ, where $P\{D\}$ is the prior probability of having CHD.

Condos and Knox [6] conducted an experimental evaluation of a prediction model, based on (3.4) above, for aiding in the diagnosis of CHD. The model was evaluated by checking how well it diagnosed patients from a known CHD group, a known healthy group, and a random sample. The samples of patients consisted of active duty or retired military men between the ages of 30 and 67 years, and the data came from three different military hospitals. Since appropriate data was not available to use (3.3), the tests of the indicators were ordered in terms of their relative diagnostic power. This provided an ordering, though not necessarily an optimal one, among a standard set of clinical tests. The criterion for evaluating the model was "misclassification probability".

Although the sample sizes were small (50, 52, and 14 patients), the overall diagnostic accuracy of the model was found to exceed 91 percent. A threshold probability of $\gamma = 0.5$ was used, and the diagnostic accuracy was found to be quite sensitive to γ. The single greatest difficulty in evaluating the model was missing data values. For this evaluation, this difficulty was avoided by eliminating the entire set and accepting smaller sample sizes.

We have considered a systematic framework for analyzing the medical diagnosis of CHD. Although here only the dichotomy of CHD vs. no CHD has been considered, an extension can be made to include various types of CHD or even multiple diseases. We have alluded to the fact that the Bayes approach is the most superior, but certainly not without shortcomings [7]. Implicit assumptions have been made regarding independence and the absence of multiple diseased patients. Furthermore, the Bayesian approach requires a substantial amount of data, and the priors can vary considerably from one locale and envircnment to another.

4. SOME OPERATIONAL MODELS FOR FEASIBILITY CONSIDERATIONS

4.1 Paramedic Utilization and System Effectiveness

Recent efforts in the area of computer-aided medical diagnosis in the context of an MDS model have, as previously mentioned, been twofold in purpose. First of all, the computer, with the ability to digest information rapidly, is thought to be a potential aid to the accuracy and duration of the diagnostic procedure. Secondly, a paramedical team with the aid of a computer, can conserve the precious time of the doctor. It is this second facet that we investigate in this section, the former having already been discussed.

Consider the diagnostic design process in Figure 1 which deals with a single decision-maker - the doctor. Closely associated with the concept of a unidimensional scale for the amount of information at stage k, I_k, is that of a unidimensional scale for diagnostic complexity C_k. C_k is to be directly related to the probability of mis-classification (or mis-diagnosis) and inversely related to I_k.

Let us once again consider Figure 3 with some additions and variations as in Figure 4. In order to conform with Section 3, we could incorporate a function $g(\cdot)$ such that $C_k \equiv g(S(k))$. At stage k, a patient arrives at MEDIC i with a symptom complex of complexity C_k. With probability $\alpha_i(C_k)$, the medic accepts the case and continues on to attempt diagnosis. With probability $1 - \alpha_i(C_k)$ the case is submitted to the team of paramedic-computer, where an update is accomplished on the patient and resubmitted to the medic - the cycle repeating itself.

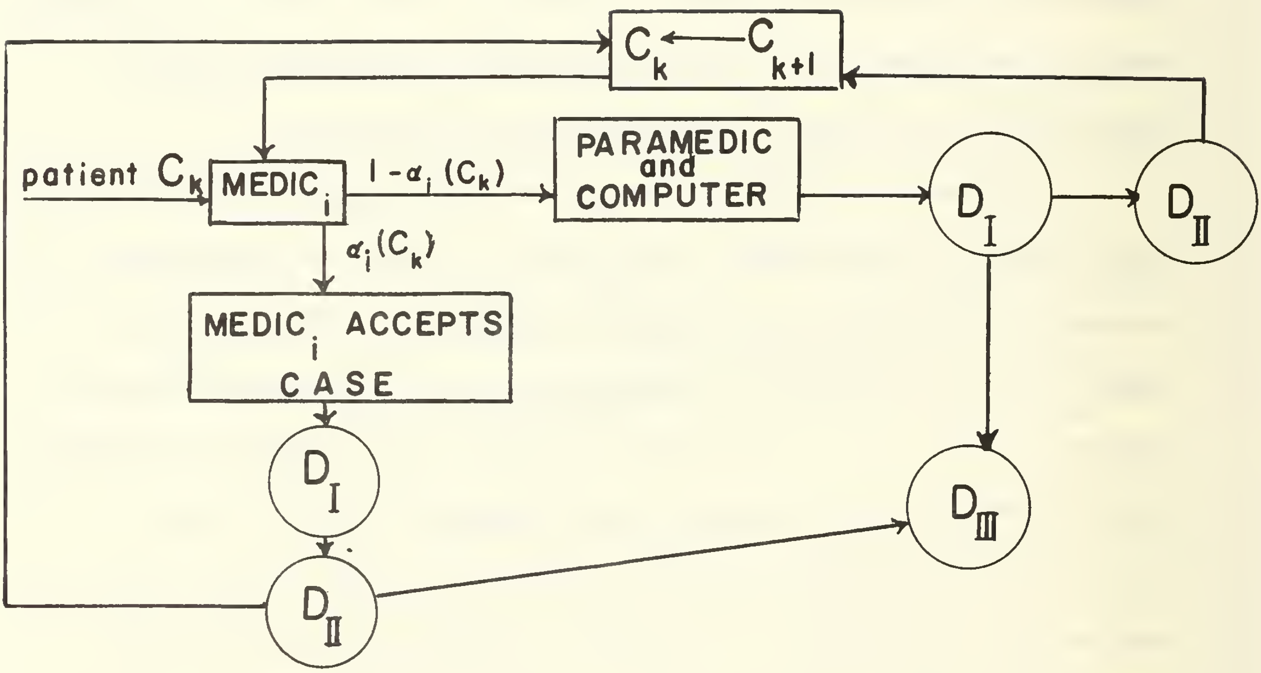

Figure 4: Medic-Paramedic Interaction

In order to quantify the degree of utilization of the paramedic-computer (and, hence, the degree of conservation of the medic), it is essential that we know something about the distribution of the random variable C_0 and, in general, the stochastic process $\{C_k, k = 0, 1, 2, \ldots\}$. We must also know the probability functions $\alpha_i(\cdot)$ for all i.

To illustrate, let us assume that $C_k \equiv C_0$ for all k, with the added simplification that the medic decides at stage 0 as to who will take the case. We assume he sticks to that decision. Let the cumulative distribution function (c.d.f.) of C_0 be F_0 and let α_i be the expected proportion of cases accepted by medic i. Thus, $\alpha \equiv \sum_{i=1}^{N} \alpha_i / N$ is the average utilization of all medics, where N is the number of medics. Thus,

$$\alpha \equiv \frac{\sum \alpha_i}{N} = \int_0^1 \left\{ \frac{\sum \alpha_i(C)}{N} \right\} dF_0(C) \equiv \int_0^1 \alpha(C)\, dF_0(C).$$

Strictly in terms of cost alone, there are savings through use of paramedics. This is partially offset by the cost of the computer. However, the conservation of the medics' valuable time compounded by the medics' ability to spend more time on truly difficult cases comprise benefits that are not readily quantifiable - yet are important.

Towards the end of considering the cost factor alone, we proceed as follows. Let $\lambda(C)$ denote the multiplicative coefficient relating the required number of paramedic man-hours to the required number of medic man-hours for a case of complexity C. Thus, a task of complexity C which requires one hour of a medic's time will require $\lambda(C)$ of a paramedic's time.

Let

C_M = cost per hour of a medic's time

C_P = cost per hour of a paramedic's time

N_M = number of medics

N_P = number of paramedics.

Thus, the cost per hour for medical personnel is simply $C_M N_M$ + $C_P N_P$. If a policy of greater utilization of paramedics was to be pursued, then the cost per hour would be

$$\alpha N_M C_M + C_P N_P + (1-\alpha) N_M C_P \lambda$$

where

$$\lambda \equiv \frac{1}{1-\alpha} \int_0^1 \lambda(C)[1-\alpha(C)]dF_0(C)$$

represents the average value of the multiplicative coefficient. Thus, the savings would be

$$(1-\alpha)N_M[C_M - \lambda C_P] - \text{cost of computer.}$$

To obtain a positive savings for personnel alone we must have $\lambda < \frac{C_M}{C_P}$.

It is important to note that λ is a function of the training and experience of paramedics and that the product λC_P is the critical quantity to be minimized if possible. Also, the variable α is for the most part a decision (or control) variable determined (implicitly or explicitly) by hospital policy.

To make a more accurate assessment of costs, one would have to delve more deeply into the sequential interactions between the medic and paramedic. Although one can obtain general estimates of α, a model which makes a serious attempt at estimating α as well as assessing qualitative aspects of medic-paramedic interaction would require simulation.

4.2 Manpower Requirements

In order to accurately assess manpower requirements, we must model the complex queueing network depicted in Figure 4.

Consider a diagnosis and treatment that takes a random number of treatments K, with treatments taking amounts of time that are successively t_1, t_2, ... The total time for treatment is, therefore,

$$T \equiv \sum_{j=1}^{K} t_j .$$

(For now, we will make no probabilistic or independence assumptions about $\{t_1, t_2, \ldots\}$ and K but do assume that the number of stages required by successive patients are indepent.) Assume an arrival process of general nature, GI_1, though not necessarily a renewal process.

Let

$P_k \equiv$ probability that a patient requires exactly k stages

$N_j(t) \equiv$ number of patients in stage j being treated at time t

$N(t) \equiv$ number of patients being treated at time t.

Thus, $$N(t) = \sum_j N_j(t).$$

If G_1 is the c.d.f. of t_1, then $N_1(t)$ is the number of people in a $GI_1/G_1/\infty$ queue.

Now, note that of all the arrivals in the interval $(0,t)$, the expected proportion that requires more than one stage is $1 - P_1$. Thus, the distribution of $N_2(t)$ is that of the number in a $GI_2/G_1*G_2/\infty$ queue where GI_2 represents a point process derived from GI_1 by choosing each point of GI_1 to be in GI_2 with probability $1 - P_1$. Similarly, $N_j(t)$ is distributed as the number in a $GI_j/G_1*\ldots*G_j/\infty$ queue where GI_j represents a point process derived from GI_{j-1} by choosing each point of GI_{j-1} to be in GI_j with probability $1 - P_1 - \ldots - P_{j-1}$, and $*$ represents the convolution operator.

The question of the joint distribution of $\langle N_1(t), N_2(t), \ldots \rangle$ is a more difficult one. If GI_1 is Poisson (rate λ), then it may be shown that $N_1(t)$, $N_2(t)$, ... are mutually independent and that $N_j(t)$ has a Poisson distribution with mean

$$\lambda(1-P_1-\ldots-P_{j-1}) \int_0^t [1-G_1*\ldots*G_j(u)]du.$$

thus,

$$EN_j(t) \to \lambda(1-P_1-\ldots-P_{j-1})E(S_1+\ldots+S_j)$$

as $t \to \infty$, where S_i is the i^{th} stage service. When $\{G_j\}$ are all identical, with $ES_j = ES$,

$$EN_j(t) \to \lambda_j E(S) \sum_{k=j}^{\infty} P_k \quad \text{as} \quad t \to \infty$$

By having estimates of the distribution of numbers of patients in different stages, one can assess the manpower requirements of a health maintenance facility.

5. SUMMARY

In this report we have attempted to provide some overview and perspective to the problem of initiating and maintaining a medical diagnostic system. Much of a theoretical nature has been presented in the literature thus far, but the state-of-the-art of applied and useful medical diagnostic systems can best be described as embryonic and a bit fragmented. The chief roadblocks at present are insufficient data and lack of substantial support by the medical community. Both of these roadblocks may best be averted at a military hospital - prototype health maintenance organization where data gathering policies can be set, enforced, and be of maximum value. The data necessary for evaluating an MDS consists first of a symptom-disease data bank with relative frequency tables relating diseases to various symptom complexes. Secondly, it consists of an adaptive operational evaluator which relates utilization of paramedic personnel to disease categories and symptom complexes. The latter includes a monitoring of queueing phenomena at the key points of the MDS.

Some chief operational considerations which have not received their due attention in the literature are a cost-benefit analysis of a medical diagnostic system and a staff-planning model for a medic-paramedic-computer team. These problems have been addressed and formulated in this report. Follow up studies are required to estimate parameters and validate. It is believed, however, that these considerations should be studied more vigorously if the idea of a computer-aided medical diagnostic system is to reach fruition.

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